Introductory Econometrics

A Modern Approach

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Even after deciding on the appropriate alternative, there is a component of arbitrariness to the classical approach, which results from having to choose a significance level ahead of time. Different researchers prefer different significance levels, depending on the particular application. There is no "correct" significance level.

Committing to a significance level ahead of time can hide useful information about the outcome of a hypothesis test. For example, suppose that we wish to test the null hypothesis that a parameter is zero against a two-sided alternative, and with 40 degrees of freedom we obtain a t statistic equal to 1.85. The null hypothesis is not rejected at the 5% level, since the t statistic is less than the two-tailed critical value of $c = 2.021$. A researcher whose agenda is not to reject the null could simply report this outcome along with the estimate: the null hypothesis is not rejected at the 5% level. Of course, if the t statistic, or the coefficient and its standard error, are reported, then we can also determine that the null hypothesis would be rejected at the 10% level, since the 10% critical value is $c = 1.684$.

Rather than testing at different significance levels, it is more informative to answer the following question: Given the observed value of the t statistic, what is the *smallest* significance level at which the null hypothesis would be rejected? This level is known as the ***p*-value** for the test (see Appendix C). In the previous example, we know the p-value is greater than .05, since the null is not rejected at the 5% level, and we know that the p-value is less than .10, since the null is rejected at the 10% level. We obtain the actual p-value by computing the probability that a t random variable, with 40 *df*, is larger than 1.85 in absolute value. That is, the p-value is the significance level of the test when we use the value of the test statistic, 1.85 in the above example, as the critical value for the test. This p-value is shown in Figure 4.6.

Since a p-value is a probability, its value is always between zero and one. In order to compute p-values, we either need extremely detailed printed tables of the t distribution—which is not very practical—or a computer program that computes areas under the probability density function of the t distribution. Most modern regression packages have this capability. Some packages compute p-values routinely with each OLS regression, but only for certain hypotheses. If a regression package reports a p-value along with the standard OLS output, it is almost certainly the p-value for testing the null hypothesis H_0: $\beta_j = 0$ against the two-sided alternative. The p-value in this case is

$$\mathrm{P}(|T| > |t|), \tag{4.15}$$

where, for clarity, we let T denote a t distributed random variable with $n - k - 1$ degrees of freedom and let t denote the numerical value of the test statistic.

The p-value nicely summarizes the strength or weakness of the empirical evidence against the null hypothesis. Perhaps its most useful interpretation is the following: the p-value is the probability of observing a t statistic as extreme as we did *if the null hypothesis is true*. This means that *small* p-values are evidence *against* the null; large p-values provide little evidence against H_0. For example, if the p-value $= .50$ (reported always as a decimal, not a percent), then we would observe a value of the t statistic as extreme as we did in 50% of all random samples when the null hypothesis is true; this is pretty weak evidence against H_0.